Comparing Profitability of Day Trading Using ORB Strategies on Index Futures Markets in Taiwan, Hong-Kong, and USA

Yi-Cheng Tsai, Mu-En Wu, Chin-Laung Lei, Chung-Shu Wu, and Jan-Ming Ho

***Abstract*—In literature, it has been shown that market behavior is the aggregation of investors responses to information. Although the markets do not respond in real time to events occur after the market, it seems that information is picked up by the market in early stage of market opening, and has an impact on market dynamics over the same day. In this paper, we present our studies on the design of timing parameters of ORB strategies in index futures markets. We first show that, based on cross-sectional analysis on 10-year historical data, trading volume and fluctuation of return on each one-minute interval of trading hours of the futures markets reach their peaks at the opening and closing of the underlying stock markets. Based on these observations, we define the active period of an index futures market to align with the underlying stock market. We test ORB strategies on the index futures of DJIA, S&P, NASDAQ, HIS, and TAIEX from 2003 to 2013. We find that by optimizing the trading timing, ORB achieves over 10% annual return with p-value no greater than 2% in each futures market. The best performance, 22.6% annual return at p-value of 1×10^{-8}, occurs in TAIEX.**

I. Introduction

Technical analysis is one of the most popular methods for developing trading strategies (Park and Irwin [4]). In contrast to fundamental analysis, which uses macroeconomics and corporate information of corresponding assets, included earning per share (EPS), sales margin, dividend yield, etc., technical analysis forecast the movement of price in the future by using present and past prices. Schulmeister [5] investigates how technical trading systems exploit the momentum and reversal effects in the S&P 500 spot and futures market. They find that technical trading systems, which use 30-minutes-prices information, perform better than technical trading systems using lower frequency information.

Profitability of technical analysis strategy has been studied extensively in the literature. Brock et al. [1], test two of the most popular trading rules, i.e., moving average (MA) and trading range break (TRB) by using 90 years of Dow Jones Index. They find significant results in profitability test in both standard statistical analysis and bootstrap techniques. Zhu and Zhou [7] modify the trading rule of MA to adjust asset allocation. Neely et al.[3] use previously studied trading rules, such as MA, to test the intertemporal stability of excess returns in the foreign exchange market. They find positive excess returns of MA during 1970s and 1980s. However, the profit opportunities of MA rules disappeared in early 1990s. They conclude that these regularities are consistent with the Adaptive Markets Hypothesis [2]. Szakmary et al. [6] investigate commodity futures markets using a monthly dataset spanning 48 years and 28 markets. They find trend following trading strategies yield positive mean excess returns net of transactions costs in at least 22 of the 28 markets.

Open Range Breakout (ORB) [8] is a commonly used trading strategy for technical trading based on momentum effect. A trader sets a predetermined threshold of upper and lower bounds to denote the open range. The trading strategy is to long (or short) a position as the market price moves beyond the upper (or lower) bound. Some ORB variants are discussed recently [9], [10], [11]. Holmberg et al.[11] showed the profitability of the ORB strategy based on normally distributed return on the day of breaking opening range. Their result shows the characteristics of increased success rate in a fair game. Borda et al. [9] considered two ORB variants based on Average True Range and Volatility Breakout, respectively, and provided the evidence of profitability of the ORB strategy in Bucharest Exchange Trade index. Cekirdekci [10] studied various trading strategies based on 30-minute opening range breakouts, and showed the profitability by back-testing on 250 stocks from various industry groups during 2005 to 2010.

In this paper, we design the variants of ORB strategies in index futures markets. The parameters of the ORB strategies are selected based on the following two observations. First, trading volume and fluctuation of return on each one-minute interval of trading hours of the futures markets reach their peaks at the opening of the underlying stock markets. Thus, we provide two measurements to measure the fluctuation of the market on each one-minute interval of the trading hours. One is per-minute mean of volume, denoted as **PMMV**, and the other is per-minute variance of return, denoted as **PMVR**. These two measurements define a time period with high volume and large fluctuation as active hours. In our experiments, we find that active hours of a futures market is the same as the opening hours of the underlying stock market. Second, the fluctuation of stock markets is influenced by the events occurred during and after the market. Although the markets do not respond in real time to events occur after the market, it seems that the information is picked up by

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the market in the early stage of market opening, and has an impact on market dynamics on the same day. Based on these two observations, we make the following hypothesis. Because the dynamic of price in the early stage of market opening reveals more information in a trading day, we may use the information of the movement of price during this period to forecast the price on the rest time on the same day.

To test this hypothesis, we set up the parameters of our ORB strategies by using the information picked up by the market in the early stage of market opening. By profitability test on the index futures of DJIA, S&P 500, NASDAQ, HSI and TAIEX from 2003 to 2013, we find that our ORB strategies in each futures markets achieve over 10% annual return with *p*-value less than 2% of *t*-test, and these results significantly reject the null hypothesis that the return of our ORB strategies equals to zero. Furthermore, the best performance in our experiments is 22.6% annual return with 1×10^{-8} *p*-value in TAIEX. In addition, we also experiment in the subperiods from 2003 to 2007 and from 2007 to 2013 to show the robustness of our ORB strategies. In both two subperiods, the best strategies in each futures markets still achieve over 10% annual return with *p*-value less than 3% of *t*-test.

Moreover, our ORB strategies performs better than the TRB strategies, which are defined by Brock et al. [1]. The concept of TRB strategies are the same with ORB. However, TRB strategies set up the parameters by using daily data. The experiment results show that there is no significant result (*p*-value less than 5%) of profitability test of TRB strategies on the index futures of DJIA, S&P 500, HSI, TAIEX in full samples. Although the best strategies of full samples test of TRB on the index futures of NASDAQ earn significant profits, there is no significant result in two subperiods tests. The annual returns of the best strategies of TRB are smaller than the annual returns of our ORB strategies in these five futures markets. Our experiment results are consistent with the findings of Schulmeister [5]. By using one-minute information of prices, our ORB strategies perform better than TRB strategies.

The rest of the paper is organized as follows: In Section II, we present the settings of parameters in our ORB strategies. In section III, we introduce the empirical data. The experimental results and discussion are given in the Section IV. Finally, Section V presents conclusions.

II. METHODOLOGY

In this section, we set up the parameters of our ORB strategies based on the economic phenomena in futures markets.

A. Using PMMV and PMVR to identify active hours

We first define the two variables **PMMV** and **PMVR** to measure the fluctuations in futures markets. The definitions of **PMMV** and **PMVR** are shown in the following.

Let $V_{t,d}$ be the trading volume in the one-minute interval t on day d, where $t_0 < t < T$, and t_0 and T are the open and closed time of the futures markets, respectively. PMMV is defined as:

$$\mathbf{PMMV}_t = (\sum_{d=1}^{N} V_{t,d})/N \tag{1}$$

where N is the total number of trading days. Let $P_{t,d}$ be the close price in the one-minute interval t on day d. Thus, the return of one-minute is denoted as

$$r_{t,d} = \log(P_{t,d}) - \log(P_{t-1,d}). \tag{2}$$

Then, **PMVR** is defined as:

$$\mathbf{PMVR}_t = Var(r_{t,d}) \tag{3}$$

B. ORB and profitability test

The trading signals of our ORB variants are described as follows: We set the resistance (support) levels as the highest (lowest) prices of the predetermined period. Thus, once the price breaks through the upper bound or drops below the lower bound, the trading signal is revealed. We consider two cases:

Case 1: If the price moves over the resistance level, it means the buying strength breaks through the selling pressure. The prices is still going to move up with the trend.

Case 2: If the price is dropping below the support level, it means the selling strength is larger than the buying pressure. Thus the price is going to move down the same as the previous trend.

To build up an ORB strategy with the intraday data, we have to determined three time-points. That are, the beginning time-point of the observed period, the end time-point of the observed period and the time-point of closing position. Because there is more information during the active hours, we set up the beginning of observed period as the beginning of active hours, denoted as t_b, and the end of active hours, denoted as t_e, to close position. The end of observed period is the probing time t_p, where $t_b < t_p < t_e$. The sufficient conditions of the buying and selling signals of day d are shown in the following:

$$P_{t,d} > \max(P_{t_b,d}, ..., P_{t_p,d}) => Buy, \tag{4}$$

$$P_{t,d} < \min(P_{t_b,d}, ..., P_{t_p,d}) => Sell, \tag{5}$$

where $t_p < t < t_e$. If there is trading signal on the day, we close the position at t_e on the same day.

Using back-testing of empirical data, we follow the profitability test described in Brock et al. [1].

III. Data

We investigate the spot month E-mini futures of Dow Jones Industrial Average Index (DJIA) in Chicago Board of Trade (CBOT), Standard & Poor's 500 (S&P) in Chicago Mercantile Exchange (CME), and NASDAQ 100 in CME. We also study two spot month futures of index, which are Hang Seng Index (HSI) in Hong Kong and Taiwan Stock Exchange Capitalization Weighted Stock Index (TAIEX) in Taiwan, in Asia. The datasets contain 1-minute intraday data. In addition to the full sample, results are presented for two subsamples divided by 2007/1/1 because of global financial crisis during 2007 to 2008. Our data set contains data of spot month E-mini futures of DJIA from 2003/1/2 to 2013/12/2, S&P from 2001/1/2 to 2013/12/2, and NASDAQ from 2001/1/2 to 2013/12/2. The data of spot month futures of HSI is from 2003/1/2 to 2013/12/2. However, because of regulation, the trading time changes from 2011/3/7. So, our experiments use the data from 2003/1/2 to 2011/3/4. We have spot month futures of TAIEX from 2001/1/2 to 2013/11/28.

TABLE I
SUMMARY STATISTICS FOR DAILY RETURNS

E-mini DJIA

Return	Full Samples	Subperiod(03-07)	Subperiod(07-13)
Number of observations	2693	978	1714
Mean	0.0002	0.0004	0.0001
SD	0.012	0.008	0.013
Skewness	-0.030	-0.040	-0.013
Kurtosis	12.745	4.766	11.207
Serial correlations			
$\rho(1)$	-0.109***	-0.049	-0.123***
$\rho(2)$	-0.029	-0.013	-0.030
$\rho(3)$	0.047**	0.037	0.046**
$\rho(4)$	-0.028	0.036	-0.037*
$\rho(5)$	-0.029	-0.067**	-0.021

TABLE II
SUMMARY STATISTICS FOR DAILY RETURNS

E-mini S&P

Return	Full Samples	Subperiod(01-07)	Subperiod(07-13)
Number of observations	3181	1465	1715
Mean	0.000085	0.000031	0.000140
SD	0.013	0.011	0.015
Skewness	-0.148	0.082	-0.227
Kurtosis	10.629	5.738	10.880
Serial correlations			
$\rho(1)$	-0.084***	-0.021	-0.114***
$\rho(2)$	-0.037**	-0.034	-0.038
$\rho(3)$	0.029	0.026	0.030
$\rho(4)$	-0.039**	-0.056**	-0.031
$\rho(5)$	-0.012	0.002	-0.018

IV. Experiment Results and Discussions

In this section, we will show experiment results, including how to identify active hours, and the profitability test of ORB. First, we look at the summary statistics of daily return in Table 1 to 5. Returns are measured as percentage differences of $\log$ of the futures. We show the results of full samples and two subperiods. In these five futures, the means of the daily return are positive only except E-mini NASDAQ in subperiod from 2003 to 2007. The biggest standard deviation occurs in E-mini NASDAQ in subperiod from 2003 to 2007, too. In full samples, all these five futures are with negative Skewness. In subperids 2007 to 2013, except HSI, all the futures are with negative Skewness probably because of the global financial crisis. However, the values of skewness are small in all these futures except in TAIEX. $\rho(i)$ is the estimated i days lag autocorrelation. The star marks *, **, and *** represent significance at the 10, 5, and 1% levels of confidence interval, respectively. In E-mini DJIA, the first order serial correlations in full samples and second subperiod are significantly negative. In other orders, the serial correlations are generally small. For Emini S&P and E-mini NASDAQ, there are significant negative serial correlations in first two orders.

TABLE III
SUMMARY STATISTICS FOR DAILY RETURNS

E-mini NASDAQ

Return	Full Samples	Subperiod(01-07)	Subperiod(07-13)
Number of observations	3181	1465	1715
Mean	0.000092	-0.00025	0.00039
SD	0.017	0.020	0.015
Skewness	-0.027	0.040	-0.112
Kurtosis	7.640	6.007	9.958
Serial correlations			
$\rho(1)$	-0.031*	0.010	-0.090***
$\rho(2)$	-0.060***	-0.091***	-0.015
$\rho(3)$	0.022	0.026	0.015
$\rho(4)$	-0.029*	-0.026	-0.035
$\rho(5)$	0.002	-0.001	0.007

TABLE IV
SUMMARY STATISTICS FOR DAILY RETURNS

HSI

Return	Full Samples	Subperiod(03-07)	Subperiod(07-11)
Number of observations	2018	989	1028
Mean	0.00045	0.00079	0.00011
SD	0.017	0.011	0.021
Skewness	-0.031	-0.225	0.032
Kurtosis	9.128	4.386	6.873
Serial correlations			
$\rho(1)$	-0.016	-0.011	-0.017
$\rho(2)$	-0.028	-0.023	-0.029
$\rho(3)$	-0.009	-0.006	-0.009
$\rho(4)$	-0.068***	0.042	-0.074**
$\rho(5)$	0.018	-0.007	0.024

TABLE V
SUMMARY STATISTICS FOR DAILY RETURNS

TAIEX

Return	Full Samples	Subperiod(01-07)	Subperiod(07-13)
Number of observations	3203	991	2211
Mean	0.00017	0.00023	0.00015
SD	0.016	0.019	0.015
Skewness	-0.219	-0.019	-0.398
Kurtosis	6.444	4.960	7.429
Serial correlations			
$\rho(1)$	-0.019	-0.035	-0.008
$\rho(2)$	0.007	0.011	0.003
$\rho(3)$	0.016	0.046	-0.006
$\rho(4)$	-0.022	0.028	-0.057***
$\rho(5)$	-0.022	-0.023	-0.021

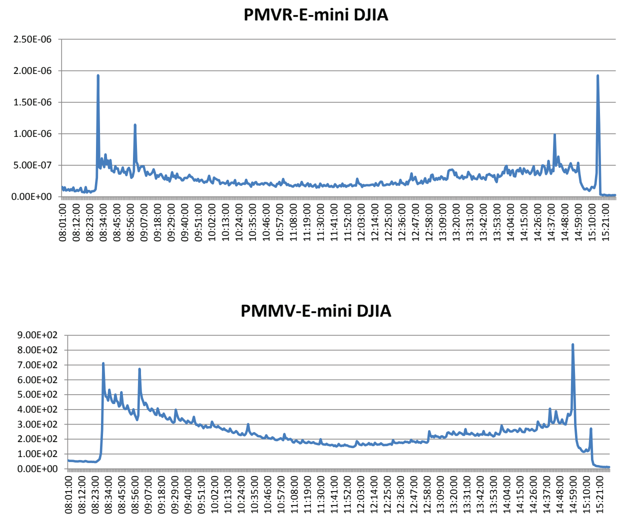

Fig. 1. **PMMV** and **PMVR** of E-mini DJIA

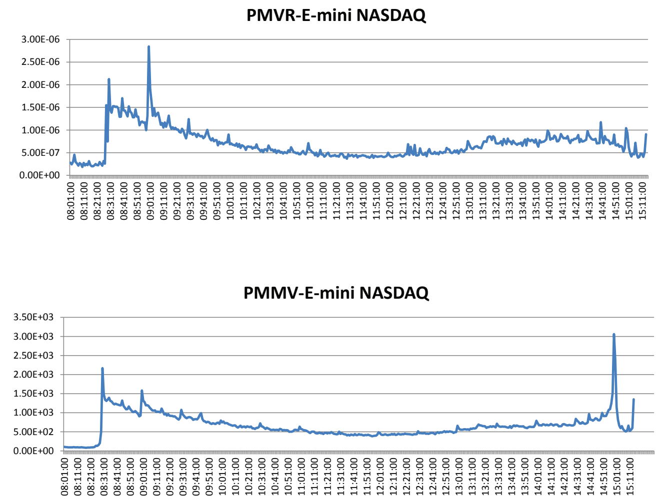

Fig. 3. **PMMV** and **PMVR** of E-mini NASDAQ

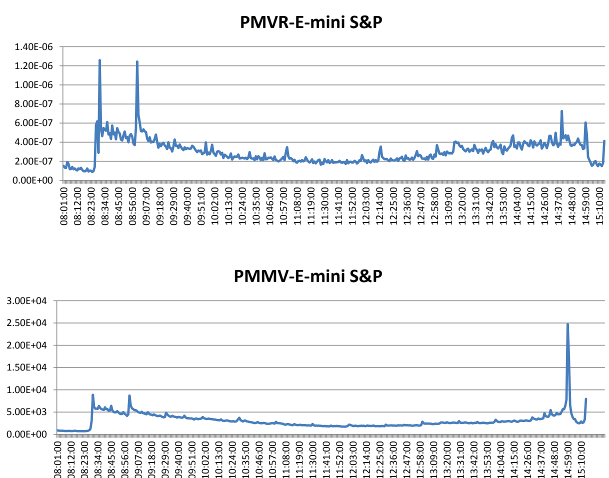

Fig. 2. **PMMV** and **PMVR** of E-mini S&P

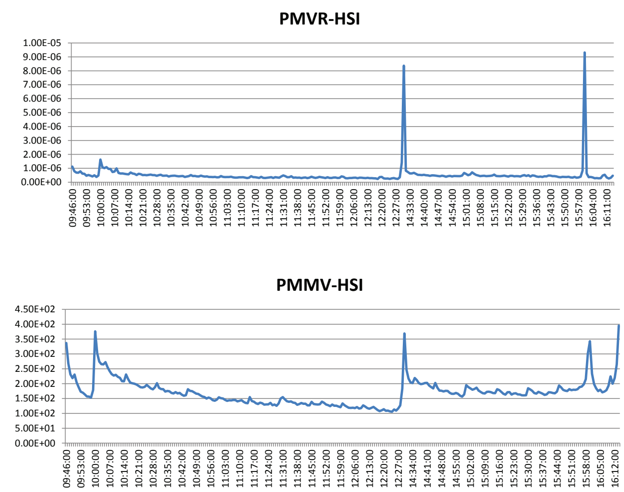

Fig. 4. **PMMV** and **PMVR** of HSI

From Fig.1 to Fig.5, we show the **PMMV** and **PMVR** on each minute of five futures. Fig.1 is the result of E-mini DJIA from 8:01 AM to 15:29 PM (local time in Chicago). Because the values of **PMMV** and **PMVR** out of this region are very small, we only show the results in this time period. There is a peak on 8:30 AM, and the values during 8:30 AM and 9:00 AM are generally lager than other time points in both **PMMV** and **PMVR**. 8:30 AM is the opening time of the underlying of E-mini DJIA. There is another peak on 15:00 PM in **PMMV**, and this time point is the close of the underlying of E-mini DJIA. There is a peak of **PMVR** on 15:15, which is the close time of E-mini DJIA. In Fig 2 and Fig. 3, which are the results of E-mini S&P and E-mini NASDAQ, we show the results from 8:01 to 15:14. We can find similar results to E-mini DJIA. There are peaks on opening and closing time of underlying markets. In Fig.4, the results of HSI show not only peaks on open (10:00 AM) and close (16:00 PM) of underlying market, but also a peak on 14:30 PM. This peak of HSI in both **PMVR** and **PMMV** is due to the lunch break from 12:30PM to 14:30 PM. In Fig. 5, the results of TAIEX show four peaks. Two are on the opening (9:00 AM) and closing (13:30 PM) time of underlying market, and the others are opening (8:46 AM) and closing (13:44 PM) time of futures market. To summarize the results of **PMVR** and **PMMV** in these five futures, there are peaks on opening and closing time of underlying market, and the values of **PMVR** and **PMMV** are larger in early stage of the opening time of underlying market. Thus, we set the

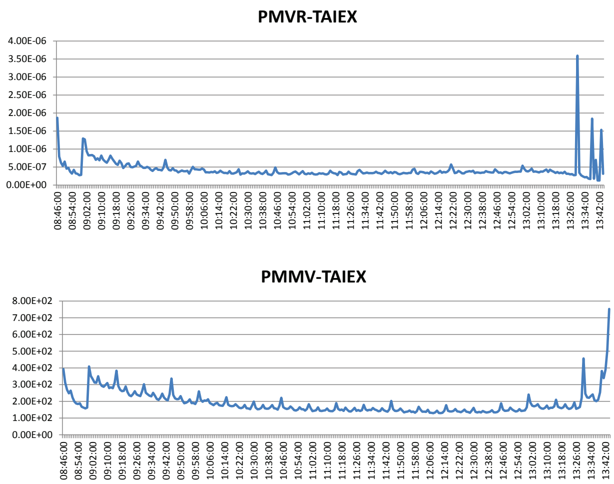

Fig. 5. **PMMV** and **PMVR** of TAIEX

active hours from the opening time of underlying market to closing time of underlying market.

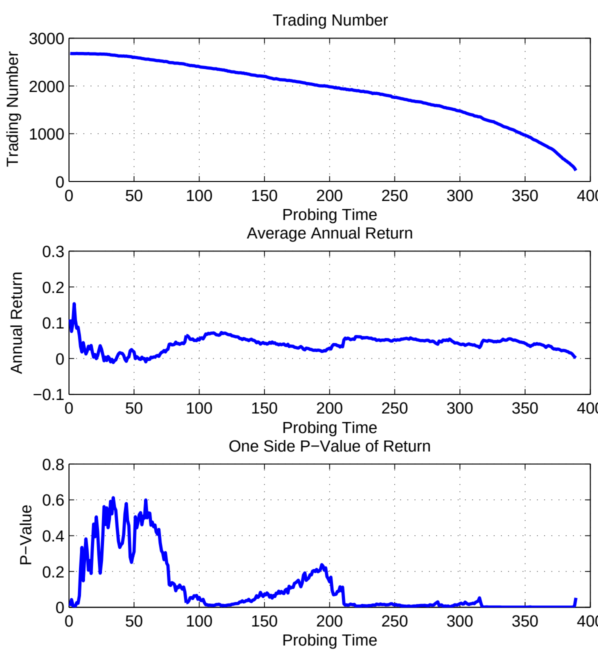

Fig. 6. Trading number, average annual return, and one side p-value in DJIA in full samples test

After setting up active hours, we use equation 4 and 5 to build up our ORB strategies with probing time as a parameter. Fig.6 shows the back-testing results in DJIA in full samples. The fist one shows the trading number of ORB. We define trading number as the number of transactions of ORB in experiment period in this paper. The trading

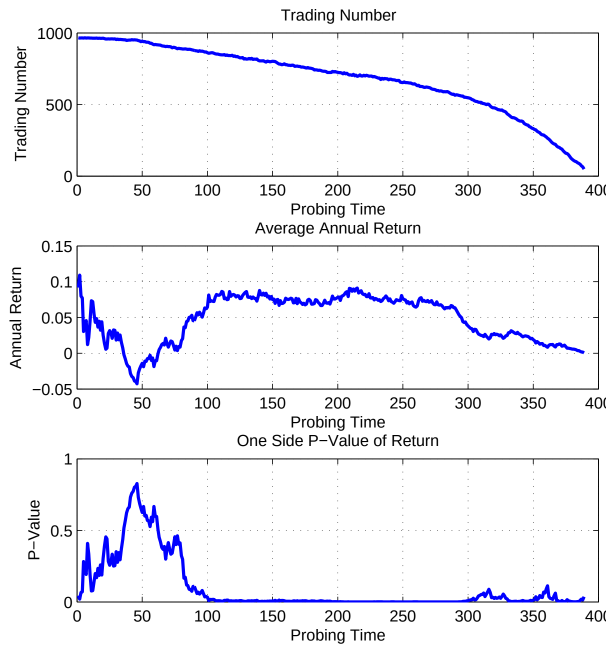

Fig. 7. Trading number, average annual return, and one side p-value in DJIA in Subperiod(03-07) test

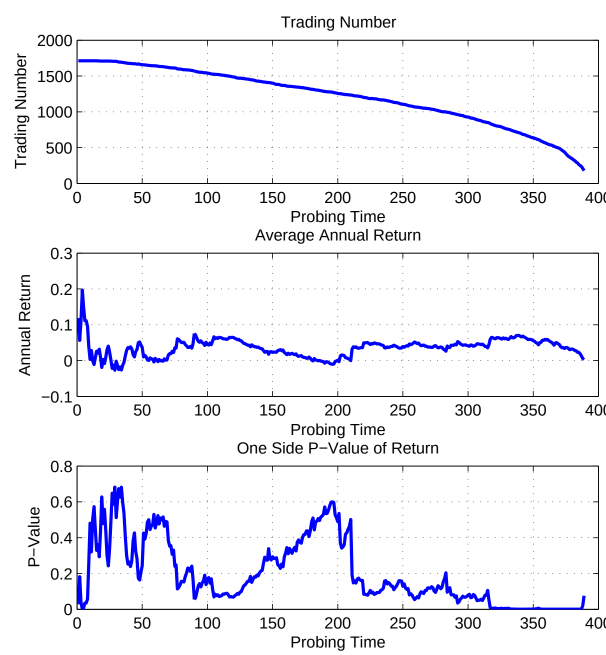

Fig. 8. Trading number, average annual return, and one side p-value in DJIA in Subperiod(07-13) test

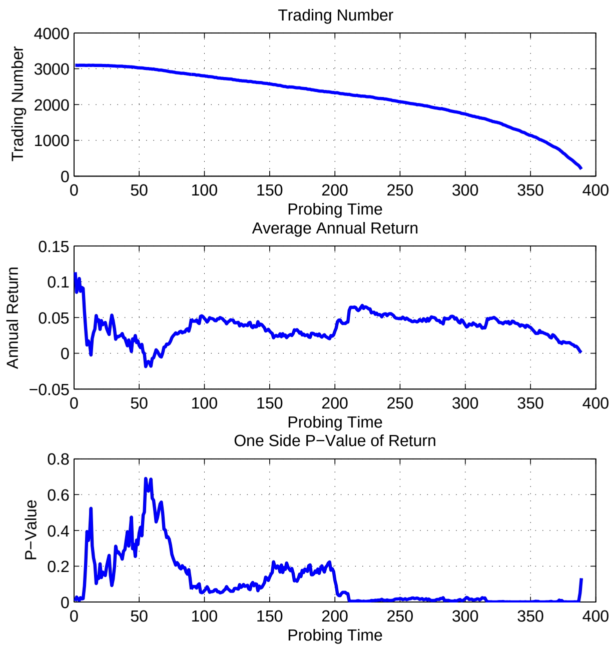

Fig. 9. Trading number, average annual return, and one side p-value in S & p in full samples test

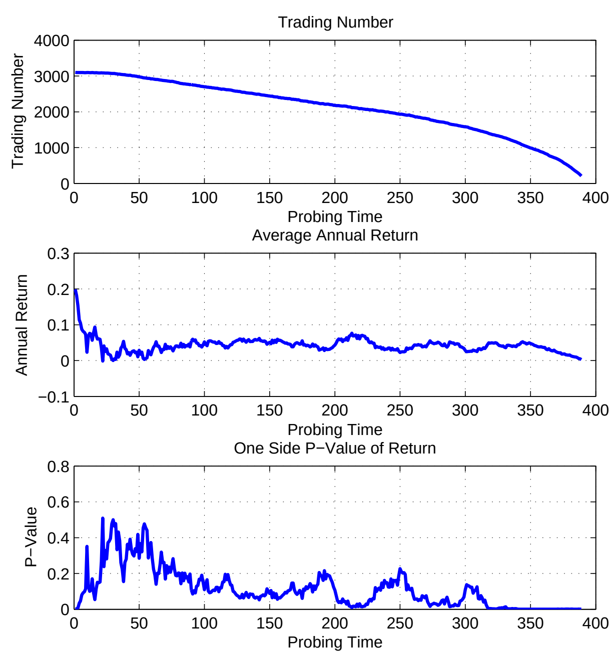

Fig. 10. Trading number, average annual return, and one side p-value in NASDAQ in full samples test

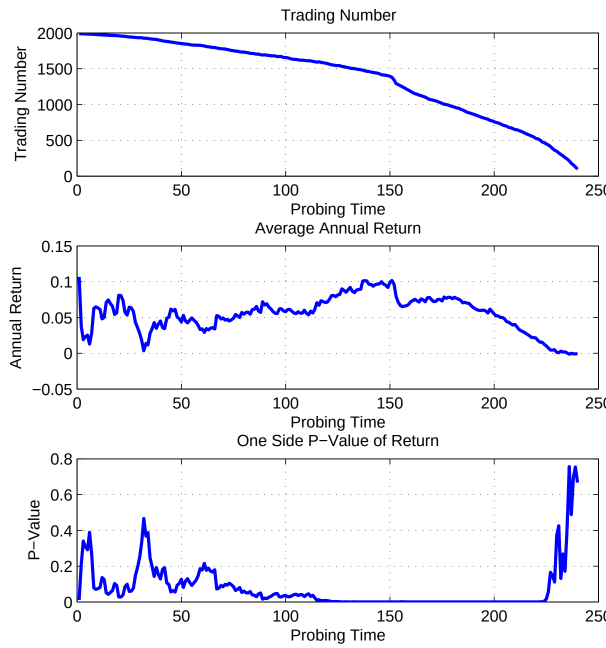

Fig. 11. Trading number, average annual return, and one side p-value in HSI in full samples test

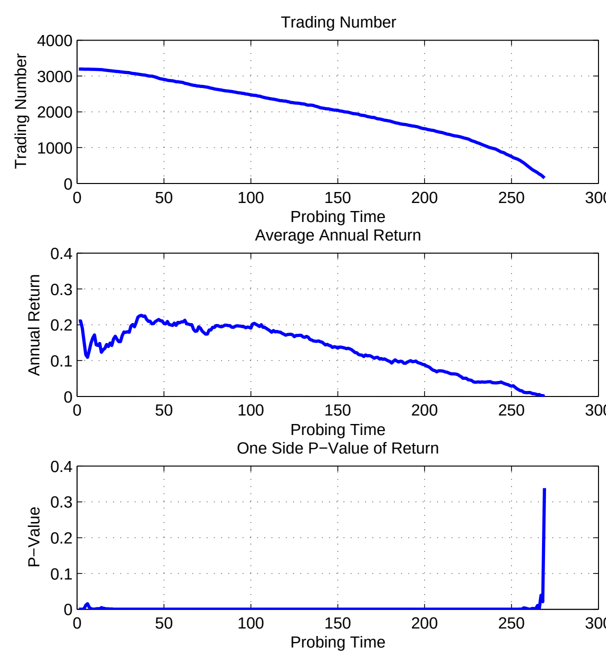

Fig. 12. Trading number, average annual return, and one side p-value in TAIEX in full samples test

number decreases when the probing time goes away from beginning time of active hours. Because when the probing time goes away from beginning time of active hours the boundary will be larger, and the probability of the price breaking out the boundary on the same day will decrease. The second one illustrates the average annual return of ORB strategies. As the economic expression of our observation, the strategies with the probing time in the early stage earn significantly high annual return. The third one is the one side *p*-value of *t*-test. The null hypothesis is that the return of ORB equal to zero. When the probing time is within five minutes, the results significantly reject the null hypothesis with *p*-value less than 0.02. Fig.7 and Fig.8 are the subperiod test in DJIA. We find that the results are similar as the full samples test in DJIA. That is, the results are robust in different time period. Because the results of subperiods are all similar to full samples, we only show the results of full samples in the rest markets. Fig.9 and Fig.10 are the results in S&P and NASDAQ, respectively. The results of ORB strategies in these two markets (S&P 500 and NASDAQ) and DJIA are similar. The probing time within 5 minutes earn highest annual return with significant *p*-value. Fig.11 shows the results in HSI. As the results in US markets, the ORB strategies earn significantly high return in early stage of the opening time of stock market. Actually, ORB strategies also earn significantly high return with probing time around 150 minutes. These results may due to the difference of market structure and market efficiency. For example, the lunch break from PM 12:30 to PM 14:30 in Hong Kong market may effect the performance of technical analysis. Moreover, the different market efficiency level of US market and Hong Kong market may result in different performance of technical analysis. Fig.12 shows the results in TAIEX. The strategies with probing time smaller than 200 minutes earn significantly high return. Table VI shows the best strategies in these markets with full samples. The best strategies in these markets are all with small probing time. The average annual returns in these markets are larger than 10% with *p*-value less than 0.02 in this period. TABLE VII and TABLE VIII are the results of subperiod test, which are consistent with the results of full samples.

In order to compare with TRB strategies, we follow the definition in Brock et al. [1], and give a brief introduction as follows: Buy (sell) signals of TRB are generated when the price larger (less) than band multiple the local maximum (minimum) of price in previous D days. When the buy (sell) signals reveal, we open the positions and hold it for ten days. In this paper, we test $2 \leq D \leq 200$ with band as 0 or 1%. The best TRB strategy in each market with full samples is given in TABLE IX. The experiments show there is no significant result (*p*-value less than 5%) of profitability test of all TRB strategies on the index futures of DJIA, S&P 500, HSI, TAIEX in full samples. Although the best strategies of full samples test of TRB on the index futures of NASDAQ earn significant profits (*p*-value= 4.19%), the annual return 5.65% is smaller than the annual return 19.9% of our best ORB strategy on the index futures of NASDAQ. In two subperiod tests of TRB, which are shown in TABLE X and TABLE XI, there is no significant result on the index futures of NASDAQ. Thus, we conclude there is no robust result of probability test of TRB in these five futures markets.

V. CONCLUSIONS

In this paper, we study the variants of ORB strategies in index futures markets. Parameters of the ORB strategies are selected based on economic observations in five markets. We use five spot month futures of equity index, including three most liquid contracts, E-mini S&P 500, E-mini NASDAQ, and E-mini DJIA to test the profitability of ORB strategies. By analysing **PMMV** and **PMVR**, we find active hours is the same as the opening and closing time of underlying market. The experimental results show that ORB strategies achieve the high annual return significantly by picking up the information in early stage of active hours. By profitability test, our ORB strategies in each futures markets achieve over 10% annual return with *p*-value less than 2% of *t*-test. The best performance, which is 22.6% annual return with 1×10^{-8} *p*-value, occurs in TAIEX. We also show the robustness by testing full and two subperiod samples. On the contrary, experiment results also show that there is no robust result of probability test of TRB in these five futures markets. The results are consistent with the findings of Schulmeister [5]. By using one-minute information of prices, our ORB strategies catch more useful information than TRB strategies, and earn more significant profits than TRB strategies.

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TABLE VI
BEST STRATEGIES IN FULL SAMPLES TEST OF ORB

Market	Probing Time (Minute)	Number of Trading	Annual Return	t-value	p-value
DJIA	4	2677	15.33 %	3.54	0.02 %
S&P	1	3096	11.33 %	2.53	0.57 %
NASDAQ	1	3099	19.9 %	3.13	0.09 %
HSI	1	1987	13.04 %	2.27	1.18 %
TAIEX	37	3038	22.62 %	5.57	0.000001 %

TABLE VII
BEST STRATEGIES IN SUBPERIOD(2001-2007) TEST OF ORB

Market	Probing Time (Minute)	Number of Trading	Annual Return	t-value	p-value
DJIA	2	964	10.9 %	2.05	2.01 %
S&P	1	1382	13.25 %	2.42	0.79 %
NASDAQ	3	1384	24.42 %	2.29	1.11 %
HSI	26	940	15.94 %	3.23	0.06 %
TAIEX	37	1419	31.16 %	4.84	0.000073 %

TABLE VIII
BEST STRATEGIES IN SUBPERIOD(2007-2013) TEST OF ORB

Market	Probing Time (Minute)	Number of Trading	Annual Return	t-value	p-value
DJIA	4	1712	19.67 %	3.22	0.06 %
S&P	4	1714	13.95 %	2.07	1.95 %
NASDAQ	1	1713	16.8 %	2.3	1.08 %
HSI	1	1015	17.55 %	1.91	2.85 %
TAIEX	106	1252	17.21 %	4.87	0.000064 %

TABLE IX
BEST STRATEGIES IN FULL SAMPLES TEST OF TRB

Market	Test(D days, band)	Number of Trading	Annual Return	t-value	p-value
DJIA	(135,0.01)	20	0.5 %	0.22	41.39 %
S&P	(5,0)	291	0.49 %	0.1	45.98 %
NASDAQ	(164,0)	87	5.65 %	1.75	4.19 %
HSI	(149,0)	56	2.75 %	1.01	15.86 %
TAIEX	(7,0)	278	9.2 %	1.59	5.69 %

TABLE X
BEST STRATEGIES IN SUBPERIOD(2001-2007) TEST OF TRB

Market	Test(D days, band)	Number of Trading	Annual Return	t-value	p-value
DJIA	(54,0.01)	5	1.22 %	0.77	24.21 %
S&P	(5,0)	177	3.58 %	0.41	34.14 %
NASDAQ	(19,0)	136	13.25 %	1.34	9.06 %
HSI	(6,0)	87	3.21 %	0.44	33 %
TAIEX	(8,0)	123	11.19 %	1.23	11.14 %

TABLE XI
BEST STRATEGIES IN SUBPERIOD(2007-2013) TEST OF TRB

Market	Test(D days, band)	Number of Trading	Annual Return	t-value	p-value
DJIA	(4,0)	159	1.96 %	0.3	38.21 %
S&P	(21,0)	85	2.64 %	0.58	28.21 %
NASDAQ	(7,0)	109	4.65 %	0.86	19.65 %
HSI	(156,0)	19	7.32 %	1.72	5.11 %
TAIEX	(7,0)	150	12.44 %	1.76	4.02 %